Neural Machine Learning II

COMP / ELEC / STAT 602, Fall 2019

Elective course, 3 credits (3 contact hours per week)

Course home page: http://www.ece.rice.edu/~erzsebet/NMLcourseII.html
(This website is also linked from the Canvas front page.)
Students are responsible for being familiar with this syllabus, and with the contents of both the above and the Canvas website, and follow the postings as the course proceeds.

Instructor: Erzsébet Merényi
Class meets: TTH 4:00pm – 5:15pm, DCH 1042
Office/Phone: DH 2082, 713-348-3595
Office hours: by appointment
Assistant: N/A
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Short course description

Advanced topics in Artificial Neural Network theories, with a focus on learning high-dimensional complex manifolds with neural maps (Self-Organizing Maps and variants, Learning Vector Quantization variants, both unsupervised and supervised paradigms). Application to data mining, clustering, classification, dimension reduction, sparse representation. Comparison with "gold standards" on data of various complexities. Examples through image and signal processing, bioinformatics, brain mapping from fMRI, mining spectral image cubes for environmental mapping and astronomy problems. The course will be a mix of lectures and seminar style discussions with active student participation, based on research publications. Strong coding skills in MATLAB, R, or C are assumed. Students will also have access to research software environment to do simulation experiments.

Pre-requisites

ELEC / COMP / STAT 502 Neural Machine Learning I., or equivalent, or instructor's permission. Further details can be found at the course web page, http://www.ece.rice.edu/~erzsebet/NMLcourseII.html under Prerequisites.

Sample Course Outline

1. Review part of COMP / ELEC / STAT 502, Neural Machine Learning I.

1.1. Review of prototype-based unsupervised learning of manifold structure with neural maps: Hebbian Learning, Self-Organizing Maps (SOM)
1.2. The basic Kohonen SOM; and basic Learning Vector Quantizers (LVQs)

2. Interpretation of Kohonen Maps for Extraction of Manifold Structure

2.1. Visualization of SOM knowledge – basics: U-matrix and variations, density map
2.2. Visualization of SOM knowledge – advanced: Connectivity Matrix and graph representation, underlying theories
2.3. Finding clusters: interpretation of the visualized knowledge, and structure extraction
2.4. Data compression and coding aspects, sparsity

3. Advanced Variants of Neural Maps and Measures of Mapping Quality

3.1. Kohonen vs Conscience SOM, neighborhood functions and metrics
3.2. Criteria of topology-preserving mapping; Measures of topology violation
3.3. Visualization and monitoring of violations, fixes
3.4. Neural Gas, Growing Self-Organizing Maps
3.5. Magnification in neural maps, and explicit control for different optimality criteria
3.6. Preferential discovery of small clusters with controlled magnification in SOMs
3.7. Distortion based and information based Self-Organizing Maps, density matching

4. Self-Organizing Maps for High-Dimensional and Complex Data

4.1. Issues related to high dimensionality and complexity of data spaces
4.2. Why and how some favorite traditional methods fail for complicated, high-dimensional data
4.3. How do SOMs deal with high-dimensional data; Applications, case studies
4.4. Comparison with classics (PCA, MDS variants, LLE-s, ISOMAP)

5. Unsupervised Learning as Support for Supervised Classification

5.1. Hybrid ANN architectures containing unsupervised and supervised learning components
5.2. Classification versus regression (parameter inference, learning underlying causes)
5.3. The use of unlabeled samples to boost performance of supervised learning (classification)

6. Evaluation of Clustering Quality and Classification Accuracy

6.1. Cluster validity indices: classics; and advanced ones, CONNindex
6.2. Evaluation of classification accuracy: sampling requirements, k-fold cross-validation, ROC curves, Kappa statistics, Wilcoxon signed ranks
6.3. Case studies

7. Intrinsic Dimensionality, Non-linear Dimensionality Reduction

7.1. Classics
7.2. Generalized Relevance Learning Vector Quantization
7.3. Neural ICA

8. Similarity Metrics for Learning, and Learning of Metrics

8.1. Feature spaces: homogeneous and inhomogeneous (mixed) feature vectors
8.2. Feature representation: homogeneous and inhomogeneous representations
8.3. Domain specificity in metric construction (e.g., divergences for functional data)

The exact course contents will be shaped from the above menu emphasizing the collective interest of the participants.

Software: Simulations and exercises can be based on Matlab, R, or C programming, and / or using my group's research software environment

The information contained in the course syllabus, other than the absence policies, may be subject to change with reasonable advance notice as deemed appropriate by the instructor.

Detailed Course Schedule

A detailed schedule of class topics will come on-line in a timely manner at the course web site http://www.ece.rice.edu/~erzsebet/NMLcourseII.html under Course Schedule along with the schedule of reading, review (home work) and presentation assignments. The materials (s.a. lecture notes and home work assignments) indicated in the Course Schedule will be downloadable from Canvas or from other designated site.

Course Materials

The course will be based on Lecture Notes, assigned papers from literature, scheduled as posted at the course web site http://www.ece.rice.edu/~erzsebet/NMLcourseII.html under Course Schedule. Copies of mandatory reading will be provided in class.
Further recommended background reading will include selected parts of the following books, available at www.amazon.com, or at the Fondren Library at Rice.

- Simon Haykin: Neural Networks. A Comprehensive Foundation. McMillan, New Jersey, 1999. (2nd Edition)
- Teuvo Kohonen: Self-organizing Maps (Springer Series in Information Sciences S.). Springer-Verlag, 2001 (3rd Edition, ISBN: 3540679219)

Objectives of the Course

1. Student understanding of concepts, and mastery, of neural manifold learning and data mining methods, and their applications to high-dimensional complex data.
2. Student mastery of neural computation, both theoretically and through software simulations.
3. Student competence in critiquing articles form literature, and communicating their own findings from neural computing exercises.

Assignments, Grading Policies and Other Logistic Requirements

Grades will be made up of the following components, with approximate weights as shown:
75% - Performance in class (presentation and analysis of assigned papers)
15% - Mini Project
10% - Homework

1. Performance in class The instructor will give an introductory lecture for each major topic, after which students will take turns presenting and critiquing articles assigned by the instructor. Demonstration of thorough understanding of theories, rigorous presentation of algorithms, evaluation of scope, significance, applicability will be expected. Demonstrations or evaluations of capabilities of published algorithms or possible improvements will, in many cases, involve the presenter's own simulations. The presenter will be required to turn in their presentation and code (as applicable) in electronic form and will receive feedback and grade points. Every student will be required to read all articles/handouts and expected to contribute to discussions lead by the paper presenter or by the instructor. This occasionally will require everyone to run simple prescribed experiments to answer a specific question and to discuss and compare results through very short informal presentations. Students will also receive feedback and grade points for these short presentations. Details of roles and requirements will be discussed in class.

2. Mini Project There will be a short (nominally 2-week) project on a focused topic, as a conclusion of the semester. Projects will be presented in the last class period. The exact

schedule and requirements as well as suggested topics will be discussed in class well ahead of time. Students will be encouraged to pursue topics aligning with their research.

3. Homework Students will be required to write and to turn in short (approximately one-page) reviews of selected papers, and turn in experiment results. The requirements of the review will be explained in class. There will be no other homework to turn in. Students are encouraged to discuss reading and / or experiments with classmates but everyone will hand in their own paper reviews or experiment documentation which they are expected to understand, and to be responsible for the quality of the writing.

3.1 Late Homework Policy Homework is due on the due date indicated in the Course Schedule. In case of technical difficulty with electronic submission you can either bring it to class or drop it in the designated wall pocket next to my office door before class. After the due date, but before the posted "late deadline", homework can be turned in for 50% credit.

Missed assignments If you must miss (or be late with) an assignment (homework, presentation) due to an extraordinary circumstance please notify me as much ahead of time as possible, and make arrangements with me for completing the missed assignment. If, in extreme emergency, you are unable to provide advance notice, please let me know as soon as possible afterwards, and I will work with you on a solution accordingly.

Expectations Regarding Honor Code, Collaboration, and Citation

In preparing assignments (presentations, reviews, project), students are encouraged to consult freely any material and anyone. However, each individual will write and turn in his or her own write-up or presentation, which they are expected to understand. In all work, students are expected to be scrupulous about proper citation of sources (where applicable), as required both as a matter of integrity and formally as a part of the Rice Honor Code.

Class Attendance and Absence Policy

Students are expected to attend all classes since 75% of the grade is composed of participation and performance in class. Students who must miss a class or assignment because of unavoidable circumstances should consult with the instructor well in advance so that alternative arrangements may be made.

University Disability Accommodation Policy

The University seeks to foster an environment of broad access and feasibly equal opportunity to education. The Office of Disability Support Services (DSS; Allen Center, Room 111; 713-348-584; adarice@rice.edu) supports and implements federal guidelines under the Rehabilitation Act of 1973 and the Americans with Disabilities Act. Students with documented disabilities requiring accommodation under Rice's established policies should consult DSS and the instructor; all such consultations and accommodations will be held confidential to the extent feasible.

Use of Machines in the Classroom

Cell phones must be turned off – or rendered silent – within the classroom. If you need to take an urgent call, please set your phone to vibration and take the call outside the room. Laptops or other small devices may be used in class only for specific class purposes. If you have an urgent need to be online for other purposes during class time, feel free to do so . . . but outside the classroom.